Home to Home Transfer Learning

Abstract

Activity recognition plays an important role in many areas such as smart environments by offering unprecedented opportunities for health monitoring, automation, security and energy efficiency. One challenge of activity recognition is the need for huge amounts of annotated data for each new physical setting. Our question is "how can we use activities learned in one space, e.g. home A, to recognize activities in another space, e.g home B?". To answer this question, we propose a new method of transferring learned knowledge of activities to a new physical space in order to leverage the learning process in the new environment. Our method called "Home to Home Transfer Learning" (HHTL) is based on using a semi EM framework and modeling activities using structural, temporal and spatial features. This method allows us to avoid the tedious task of collecting and labeling huge amounts of data in the target space, and allows for a more accelerated and more scalable deployment cycle in the real world. To validate our algorithms, we use the data collected in several smart apartments with different physical layouts.

Introduction

With remarkable recent progress in sensor technology and machine learning techniques, activity recognition is becoming an integral part of many pervasive computing systems and smart environments. A smart environment typically contains many embedded sensors such as motion sensors that provide opportunities for health monitoring, automation, and energy efficiency based on activity recognition and inferring users behaviors from the observations (Cook and Das 2004). For example, Activity recognition in smart environments can be used to track the location and activities of residents, monitor the daily routines of people with memory deficits, generate reminders, react to hazardous situations, and in general to respond to residents' needs in a context-aware way (Wren and Munguia-Tapia 2006).

There have been a number of methods for recognizing activities, such as naive Bayes (Brdiczka, Maisonnasse, and Reignier 2005), decision trees (Maurer et al. 2006), Markov models, dynamic Bayes networks, and conditional random fields (Kautz et al. 2002), (Philipose et al. 2004). None of these approaches address the issue of transferring the learned knowledge of activities to new contexts in order to make the systems more scalable. Instead they learn the model of each environment separately. By ignoring what has been learned in other physical settings, we are faced with a redundant computational effort to learn a new model. An even greater burden is placed on the user of smart environment, who must collect and annotate sufficient data to train the recognition algorithms. Our testbeds have required at least one hour of an expert's time to annotate a single day's worth of sensor data. This particularly becomes problematic if we are targeting a deployment in the home of an older adult. Therefore it is beneficial to develop models that can exploit the knowledge of learned activities by employing it in new spaces, thereby reducing or eliminating the need for data annotation and achieving an accelerated learning pace.

Exploiting the knowledge gained in one problem and applying it to a different but related problem is called transfer learning (Raina, Ng, and Koller 2006)(Caruana 1997). It is a hallmark of human intelligence, and has been vastly studied in the literature (Pan and Yang 2008), but it has been applied to activity recognition in very few cases.

In our previous work, we have shown how to transfer the activity models learned for one person to another (Rashidi and Cook 2009b). Zhang et al. (Zheng, Hu, and Yang 2009) have developed a model that maps different types of activities to each other (e.g. sweeping to cleaning) by learning a similarity function via a Web search. Our goal is to transfer activities between different physical spaces with different residents. Kasteren et. al (T.L.M. van Kasteren and Krose 2008) describe a simple method for transferring the transitional probabilities of Markov models for two different spaces. By reducing activity models to two simple HMMs, their work does not address how activities in a target context can be found using knowledge from the source space except for the transitional probabilities, and they ignore most of the activities' important features such as the activity's structure and related temporal features. They also manually map the sensors from source to target space, which is done automatically in our approach. More importantly, they assume that the structure of HMMs is given and pre-defined, but in our model we make no assumption about the structure of the activities in the target space. The activity model in our work is much more sophisticated, and is based on using structural, temporal and spatial features of activities.

The remainder of this paper is organized as follows. First we describe our two stage approach in more detail, wherein the first stage of our algorithm mines target data and extracts activity models from both spaces, and the second stage maps activity models from source to target environment using a semi EM framework. Next we present the result of our experiments on the data obtained from three smart apartments, and finally we will end the paper with our conclusions and discussion of the future works.

Model Description

Our objective is to develop a method that can transfer learned activities across different physical spaces. We assume that labeled activity data is available in the source space S, and the objective is to use such a knowledge to learn the activity labels in a target space T where the physical aspects of the space and the sensors may be different. We assume that the nature of the problem is "inductive transfer learning" or "self taught" (Pan and Yang 2008), i.e. we have labeled data in the source domain, and none or few data labels are available in the target domain. This allows us to reduce several weeks or months of data collection and annotation in the target space to only a few days of data collection. Our ultimate objective is to be able to correctly recognize activities in the target space. By using our method, labeled target activity data becomes available that can be consumed by conventional learning algorithms to perform activity recognition, or can be used as a baseline for other techniques such as active learning techniques.

The input data is a sequence of sensor events e in the form of $e = \langle ts, s, l \rangle$ where ts denotes a timestamp, s denotes a sensor ID, and l is the activity label, if available. Each sensor is tagged with its associated room name (e.g. kitchen) which we will refer to as a location tag L. We define an activity as $a = \langle \mathcal{E}, l, t, d, \mathcal{L} \rangle$ where $\mathcal{E}$ is a sequence of n sensor events $\langle e_1, e_2, ..e_n \rangle$, l is its label (if available), t and d are the start time and duration, and $\mathcal{L}$ represents the set of location tags where a has occurred.

In our notation we consider $\mathcal{A}_S$ as the set of source activities, $\mathcal{A}_T$ as the set of target activities, $\mathcal{S}_s$ as the set of source sensors, and $\mathcal{S}_T$ as the set of target sensors. In order to be able to map activities, we need to find a way to map the source sensor network to the target sensor network i.e. we're looking for the mapping $\acute{\mathcal{F}}(\mathcal{S}_S) = \mathcal{S}_T$, as the source sensors will have different locations and properties than the target sensors. Based on using activity features and also $\acute{\mathcal{F}}$, we will find the activity mapping function $\mathcal{F}(\mathcal{A}_S) = \mathcal{A}_T$.

The extent to which activity $a_i \in \mathcal{A}_S$ maps to activity $a_j \in \mathcal{A}_T$ is reflected in matrix M, where $M[i, j] \in [0..1]$ shows the probability that activity a_i and a_j have the same label. Similarly, a second matrix $m[p, q] \in [0..1]$ shows the probability that sensor $s_p \in \mathcal{S}_S$ maps to sensor $s_q \in \mathcal{S}_T$ based on their location and their role in activity models. Note that the mappings need not to be one to one, due to the differences in the number of sensors and number of activities in the source and target spaces.

Our model performs activity transfer from a source space to a target space in several stages (Figure 1). First, labeled data from the source space and unlabeled data from the target space are processed in order to extract the activity models in each space. In the source space, each contiguous sequence of sensor events with the same label is converted to an activity. To reduce the number of activities and find a canonical mapping, similar activities are consolidated together to represent a "template activity". To avoid mapping irrelevant sensors, a filter feature selection method based on mutual information(Guyon and Elisseeff 2003) is used to remove the irrelevant sensors for each template activity. In the target space the data is mined to find unlabeled activity patterns. Activities are then consolidated using an incremental clustering method. If any labeled data is available in the target space, it can be used to refine the target activity models.

In the next step, source activity models are mapped to the target activity models. First the activities' initial mapping probabilities are computed based on structural, temporal and spatial similarities. The sensors' initial mapping probabilities are assigned based on a simple spatial similarity measure. After initialization, the algorithm starts the semi-EM framework in an iterative manner. First, the sensor mapping probabilities are adjusted based on the activity mapping probabilities, next the activity mapping probabilities are adjusted based on the updated sensor mapping probabilities. This continues until no more changes are perceived or until a user defined number of iterations is reached. A target activity's label is chosen to be the same as the source activity's label that maximizes the mapping probability. We will provide a more detailed description of each of the above steps in the following subsections.

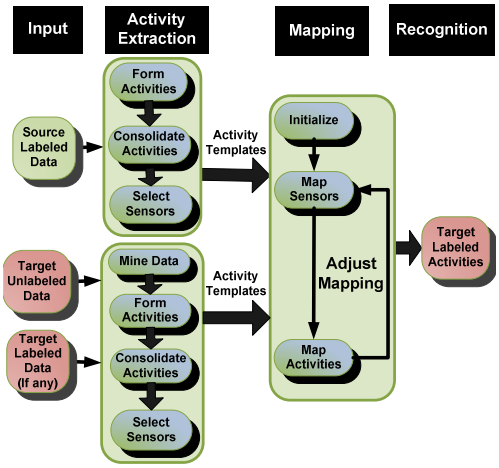


Figure 1: Main components of HHTL for transferring activities from a source space to a target space.

Activity Extraction

The first step of the HHTL algorithm is to extract the activity models from the input data. In the source space, each contiguous sequence of sensor events with the same label is converted to an activity. The start time of the activity is the timestamp of its first sensor event, while its duration is the difference between its last and first timestamps. Due

to the prohibitively large number of extracted activities and possible similarity among them, it is necessary to combine similar activities together as an "activity template". This allows for a more efficient canonical mapping from source to target instead of mapping a large number of activities with only minor differences. The activity template for a set of activities is an activity formed by merging activities' sensors, durations, and start times where the merged start times and durations form a mixture normal distribution. All the source activities that have the same label will be consolidated into one single activity template.

After similar activities are consolidated together, we need to perform sensor selection for each activity template by preserving only relevant sensors. This allows us to map only relevant sensors and avoid mapping irrelevant sensors as noise. Our sensor selection method is a filter feature selection method based on mutual information (Guyon and Elisseeff 2003). For each activity template a and each sensor s we define their mutual information $MI(s,a)$ as in Equation 1. It measures their mutual dependence and shows how relevant is sensor s in predicting the activity's label. Here $P(s,a)$ is the joint probability distribution of s and a, while $P(s)$ and $P(a)$ are the marginal probability distributions, all computed from the sensor and activity occurrences in the data. A high mutual information value indicates the sensor is relevant for the activity, we simply consider sensors with a mutual information above the midpoint (0.5) as relevant, otherwise they will be discarded.

$$MI(s,a) = P(s,a) * \log \frac{P(s,a)}{P(s)P(a)} \quad (1)$$

To extract meaningful structure from unlabeled target data, we perform data mining on the input data. First we partition the input data into activities. A sensor event $e_1 = \langle ts_1, s_1, l_1 \rangle$ and a successor sensor event $e_2 = \langle ts_2, s_2, l_2 \rangle$ are part of the same activity if $L_{s_1} = L_{s_2}$, i.e. if both sensors are in the same location. Such a local partitioning allows us to have a baseline for finding individual activities. This approach is based on the intuition that occurrences of the same activity are usually within the same location (such as preparing meal in the kitchen, grooming in the bathroom, etc), and more complex activities occurring in different locations can be composed of those basic activities. Notice that as we only have access to limited input data (perhaps a few days or even a few hours), we cannot use conventional activity discovery methods such as frequent or periodic sequence mining methods (Rashidi and Cook 2009a) to find activity patterns in the data. Therefore exploiting the spatial closure can be a way to overcome this problem. After partitioning data into the initial activities, we consolidate those activities by grouping together similar activities into an activity template. To combine activities together, we use an incremental clustering method (Can 1993), such that each activity is assigned to the most similar centroid if their similarity is above threshold ς, and then the centroid is recomputed . Otherwise the activity forms a separate cluster. The centroid is represented as an activity template. At the end all the activities in one cluster are consolidated together and the sensor selection is carried out. For two activities a_i and a_j, their similarity $\Upsilon(i,j)$ is defined as in Equation 2.

$$\Upsilon(i,j) = M_t[i,j] + M_d[i,j] + M_{\mathcal{L}}[i,j] + M_S[i,j] \quad (2)$$

In above equation, M_t refers to start time mapping (if the two activities happen at similar times, e.g. both around noon), M_d refers to duration mapping (if the two activities have similar durations), $M_{\mathcal{L}}$ refers to location mapping (if the two activities happen in similar locations, e.g. both in the kitchen), and M_S refers to structure mapping (if the two activities have similar structure in terms of sensors). We normalize $\Upsilon(i,j)$ to fall within the range $[0..1]$. For simplicity, we have chosen the mappings to have equal effects, however it's possible to define $\Upsilon(i,j)$ as a weighted average.

As mentioned, the start times are in form of a mixture normal distribution with means $\Theta = \langle \theta_1..\theta_k \rangle$. We represent start time θ in an angular form Φ measured in radians instead of a linear representation. This allows for time differences to be represented correctly (2:00 am will be closer to 12:00 pm rather than 5:00 am). Then the similarity between the two start time distributions will be as in Equation 3.

$$M_t[i,j] = \max_{\substack{\theta_1 \in \Theta_i \\ \theta_2 \in \Theta_j}} (1 - \frac{|\Phi_{\theta_2} - \Phi_{\theta_1}|}{2\pi}) \quad (3)$$

Duration mapping is calculated as in Equation 4 where durations are in form of a mixture normal distribution with means $\Gamma = \langle \gamma_1..\gamma_k \rangle$.

$$M_d[i,j] = \max_{\substack{\gamma_1 \in \Gamma_i \\ \gamma_2 \in \Gamma_j}} (1 - \frac{|\gamma_2 - \gamma_1|}{\max(\gamma_2, \gamma_1)}) \quad (4)$$

To compute $M_{\mathcal{L}}$ we use Equation 5 which is the Jaccard similarity coefficient for the sets of locations of the two activities. A similar Jaccard similarity coefficient based on similar sensors is defined for the structure mapping M_S in Equation 6.

$$M_{\mathcal{L}}[i,j] = \frac{|\ \mathcal{L}_i \bigcap \mathcal{L}_j\ |}{|\ \mathcal{L}_i \bigcup \mathcal{L}_j\ |} \quad (5)$$

$$M_S[i,j] = \frac{|\ \mathcal{E}_i \bigcap \mathcal{E}_j\ |}{|\ \mathcal{E}_i \bigcup \mathcal{E}_j\ |} \quad (6)$$

Mapping Sensors and Activities

After the activity models for the source and target space have been identified, the source activity templates are mapped to the target activity template. The first step is initializing the sensor and activity mapping matrixes, m and M. The initial values of the sensor mapping matrix $m[p,q]$ for two sensors s_p and s_q is defined as 1.0 if they have the same location tag, and as 0 if they have different locations tags. The initial value of $M[i,j]$ for two activities $a_i \in \mathcal{A}_S$ and $a_j \in \mathcal{A}_T$ is obtained based on exploiting related spatial and temporal information and also prior activity label information (if available), as in Equation 7. Note that in Equation 7 the first case applies to the few labeled target activities, while for the majority of the target activities the second case is applied.

$$M[i,j] = \begin{cases} 1.0 & if \quad l_i = l_j \\ \Upsilon(i,j) & otherwise \end{cases} \tag{7}$$

For computing subsequent mapping probabilities, we use an EM like framework by estimating the mapping probabilities in an iterative manner. First, the sensor mapping probabilities are computed; and in the next step the activity mapping probabilities are maximized based on the sensor probabilities. Though this model doesn't exactly reflect an EM algorithm, however due to its iterative manner and likelihood estimation in two steps, we call it a semi-EM framework.

To compute sensor mapping probabilities $m[p,q]$ for sensors $s_p \in \mathcal{S}_s$ and $s_q \in \mathcal{S}_T$, we rely on activities in which s_p and s_q appear in, as in Equation 8. The learning rate α refers to how fast we want to converge on the new values, while $m^n[p,q]$ and $m^{n+1}[p,q]$ refer to the current and updated values of $m[p,q]$ in iteration n and $n+1$, respectively.

$$m^{n+1}[p,q] = m^n[p,q] - \alpha * \Delta m[p,q] \tag{8}$$

$$\Delta m[p,q] = m^n[p,q] - \frac{1}{|X_p||Y_q|} \sum_{a_i \in X_p} \sum_{a_j \in Y_q} M[i,j] \tag{9}$$

$$\begin{aligned} X_p &= \{a_i \in \mathcal{A}_S | s_p \in \mathcal{E}_i\} \\ Y_q &= \{a_j \in \mathcal{A}_T | s_q \in \mathcal{E}_j\} \end{aligned} \tag{10}$$

In Equation 9, X_p and Y_q for sensor p and q give us all the activities in which the sensors appear. This means that those activities which do not include a given sensor will not contribute to that sensor's mapping probability.

In the next step, to adjust the mapping probability between each two activities, we use Equation 11 to account for the updated sensor mappings. Here $M^n[i,j]$ and $M^{n+1}[i,j]$ refer to the current and updated values of $M[i,j]$ in iteration n and $n+1$, respectively.

$$M^{n+1}[i,j] = M^n[i,j] - \alpha * \Delta M[i,j] \tag{11}$$

$$\Delta M[i,j] = M^n[i,j] - \frac{1}{|\mathcal{E}_i|} \sum_{s_p \in \mathcal{E}_i} \max_{\substack{q \\ s_q \in \mathcal{E}_j}} m[p,q] \tag{12}$$

The above procedure for computing sensor mapping probability and activity mapping probability is repeated until no more changes are perceived or until a pre-defined number of iterations is reached. Next, the labels are assigned to the target activities. To assign labels to the target activities and also find sensor mappings, we use Equation 13, 14, and 15 which provide us with the mapping functions $\mathcal{F}$ and $\acute{\mathcal{F}}$ as well as the assigned label l_{a_j} for an activity $a_j \in \mathcal{A}_T$.

$$\mathcal{F}(a_i) = \max_{a_j}(M[i,j]) \tag{13}$$

$$\acute{\mathcal{F}}(s_p) = \max_{s_q}(m[p,q]) \tag{14}$$

$$l_{a_j} = l_{a_i} \quad s.t. \quad M[i,j] = \max_k(M[k,j]) \tag{15}$$

Experiments

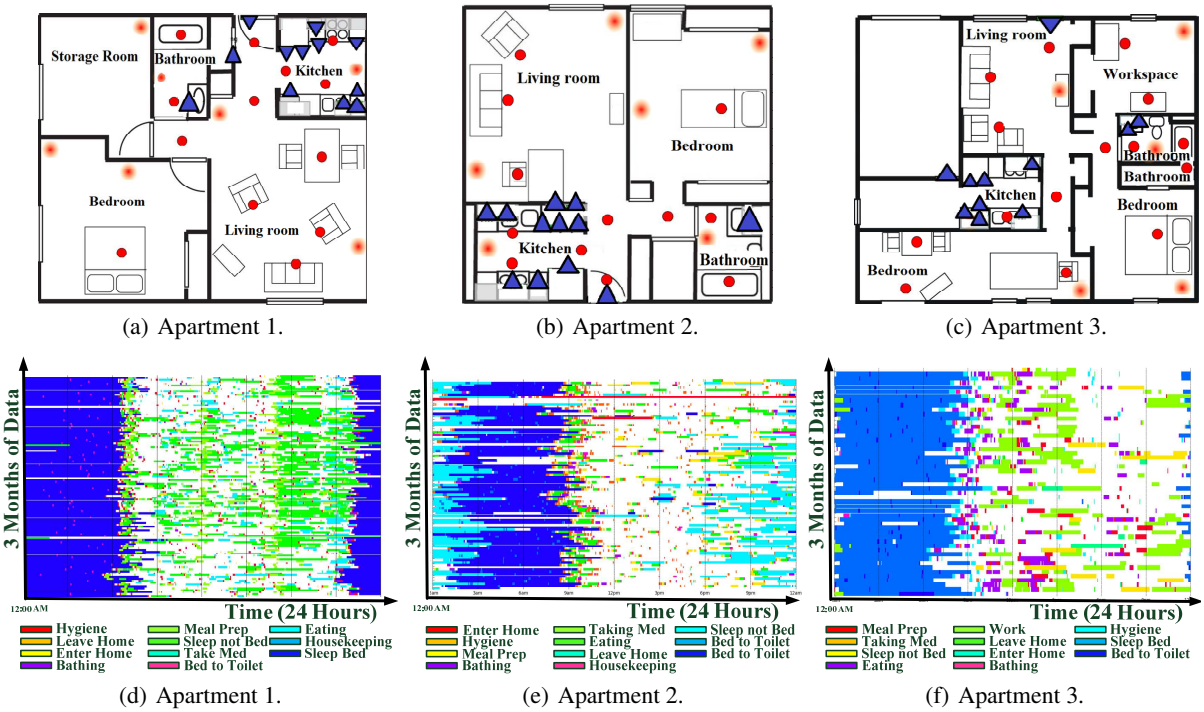
We evaluated the performance of HHTL using data collected from three different apartments during a 3 month period. Each apartment is equipped with motion sensors and contact sensors which monitor the open/closed status of doors and cabinets. The layout of the apartments including sensor placement and location tags are shown in Figure 2(a), Figure 2(b) and Figure 2(c). The apartments have different layouts: the third apartment has 2 bedrooms, 2 bathrooms and a workspace, while the first and second apartments have 1 bedroom and 1 bathroom.

The residents also have quite different schedules, as can be seen in activity distributions in Figures 2(d), 2(e) and 2(f). For example, in the first apartment housekeeping is performed each Friday, while in the second apartment it's performed once a month, and in the third apartment the housekeeping activity is replaced by work activity. Each of the three datasets was annotated with activities of interest for the corresponding resident and apartment. A total of 11 activities were noted in each case which include bathing, bed-toilet transition, eating, enter home, housekeeping (for the third apartment this is replaced by "work"), leave home, meal preparation, personal hygiene, sleeping in bed, sleeping not in bed (relaxing) and taking medicine.

We ran our algorithm on each pair of apartments, resulting in six different transfer learning problems. In each setting, we used 3 months of source labeled data, 1 to 14 days of target unlabeled data, and 0 to 3 days of target labeled data.

The first step, activity extraction, resulted in a considerable reduction in the number of activities. In particular 3384, 2602, and 1032 activity instances from the first, second and the third apartments were represented by as few as 11, 10 and 9 activity templates. The reason that we have obtained less templates than the 11 predefined activities in the second and third apartment is that the "eating" activity was done rather in an erratic way and in different locations, therefore our sensor selection algorithm didn't choose any specific sensor for that activity, and as a result the activity was eliminated. The same applied for "taking medicines" in third apartment. This shows how our algorithm can avoid mapping very irregular activities. It also shows how the algorithm condensed the activity instances into a compressed representation, as we approximately obtained the 11 predefined activities. During activity extraction, also the number of sensors for each activity template was reduced from an average of 32.13 sensors to 1.94 sensors, as the algorithm removed the irrelevant sensors and preserved only the relevant sensors. This shows that for each activity a few key sensors can be used to identify the activity, e.g. taking medicine can be identified by the cabinet sensor where the medicines are kept.

Figure 3 shows the number of discovered activity templates for the target data. For example, using three days of unlabeled target data and no labeled target data, we discovered 8, 7, and 7 activity templates for the first, second and third apartments, respectively. The similarity threshold ς in those experiments was set to the midpoint 0.5. The reason that fewer activity templates are discovered is because some similar activities might be merged into one activity, such as



(a) Apartment 1. (b) Apartment 2. (c) Apartment 3.

(d) Apartment 1. (e) Apartment 2. (f) Apartment 3.

Figure 2: Figures (a-c) show sensor map and location tags for each apartment. Circle and triangles on the map show motion sensor and contact sensors. Figures (d-f) show distribution of residents' activities per each day (horizontal axis) for 3 months (vertical axis).

relaxing and eating which happen at similar times and similar places. Also for some other activities it is not very easy to discover them from only a few days of data, such as housekeeping which happens quite rarely compared to other activities; and even if it happens to be in the data, because of its erratic nature and occurring all over the home, it is not very easy to be discovered.

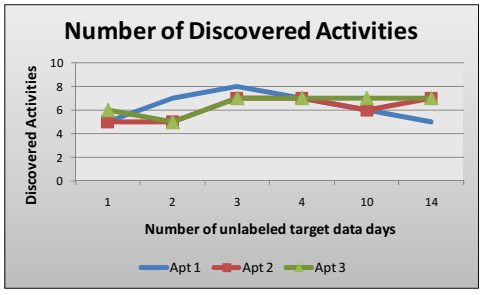


Figure 3: Number of discovered activities in the target space.

In the next step the source activities were mapped to the target activities. In order to be able to evaluate the mapping accuracy of our algorithm, we embedded the actual labels of target activities in data. This label is not used during training, rather it's only used at the end to verify the correctness of the results. The mapping accuracy is defined as number of target activities which their assigned label matches the actual embedded label. Figure.4 shows the mapping accuracy for different amounts of unlabeled target data and no labeled target data, in several different settings. It's interesting to note that transferring activities from a bigger apartment such as the third apartment to smaller apartments such as the first apartment leads to better results (e.g. %83 vs. %67 for 3 days of unlabeled data). One explanation can be the lack of certain spaces in smaller apartments, such as the workspace in the first and second apartments. It should be noted that some activities might not be present in both spaces, such as working or housekeeping. Also transfer between the first and second apartment produced relatively satisfactory results, as those two apartments have a more similar layout and functional structure.

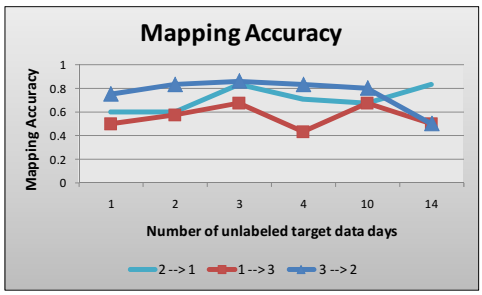


Figure 4: Mapping accuracy in several different settings.

We tested two of our own activity recognition algorithms on the transferred labeled data. The first algorithm is a near-

est neighborhood (NN) algorithm based on the similarity measure in Equation 2. The second algorithm is a standard hidden Markov model (HMM). The models almost performed the same with the nearest neighborhood algorithm sometimes slightly outperforming HMM due to its use of temporal and spatial features. Using the embedded labels we define the recognition rate as the percentage of sensor events predicted with the correct label. Figure. 5 shows NN's recognition rate based on mapping from apartment 3 to 1 using 0 and 1 day of labeled target data. Figure. 6 shows recognition rate based on mapping from apartment 2 to 1 for both NN and HMM. Our results show that despite using little to no labeled target data, and having different layouts and schedules, both algorithms still perform recognition in a target space using data from a source space.

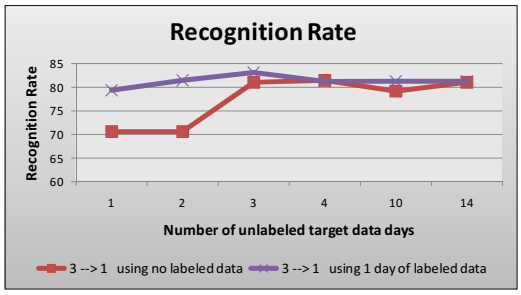


Figure 5: Nearest neighborhood's recognition rate based on mapping from apartment 3 to 1 using 0 and 1 day of labeled target data.

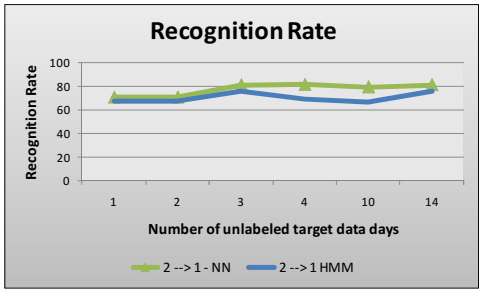


Figure 6: Recognition rate based on mapping from apartment 2 to 1 for nearest neighborhood and HMM.

Conclusion

This paper introduces a method of transferring learned activities from one physical space to another, in order to avoid the time consuming task of data annotation for each new physical space and to achieve a more accelerated deployment process. Our experiment results show that it's possible to recognize activities using no labeled data from the target space, and despite the fact that the apartment layouts and residents schedules were different. In the future, we intend to combine this method with adaptive and active learning methods in order to be able to enhance the results over time. We also want to develop algorithms that can map activities from environments with totally different functionalities, such as from a workplace to a residential space.

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